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Impacts of rising temperature, carbon dioxide concentration and sea level on wheat production in North Nile delta

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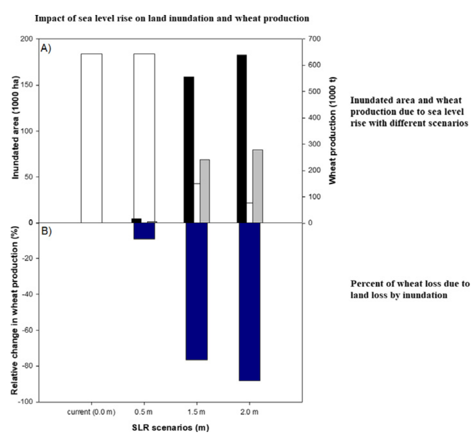
HIGHLIGHTS

- Integrated impacts of T and CO_2 on wheat yield received little attention in Egypt.
- DSSAT models showed a robust calibration with a recent high yielding wheat cultivar.
- A SLR by 2.0 m decreased the agricultural land and wheat production significantly.
- Higher levels of CO_2 alleviated impacts of temperature on wheat yield.
- Misr3 is a high yielding cultivar responding to elevated T with higher CO_2 levels.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change poses a serious threat to arid and low elevation coastal zones. Kafrelsheikh governorate, as a large agricultural and coastal region on the Egyptian North Nile Delta, is one of the most vulnerable areas to higher temperature and global sea level rise. Two DSSAT wheat models (CERES and N-Wheat) were calibrated using a local cultivar (Misr3) grown under irrigated conditions in Egypt. Experimental data of two successive growing seasons during 2014/2015 and 2015/2016 were used for calibration using different treatments of irrigation, planting dates and fertilization. Both models simulated the phenology and wheat yield well, with root mean square deviation of <10%, and d-index > 0.80. Climate change sensitivity analysis showed that rising temperature by 1 °C to 4 °C decreased wheat yield by 17.6%. However, elevated atmospheric CO_2 concentrations increased yield and could overtake some of the negative temperature responses. Sea level rise by 2.0 m will reduce the extent of agricultural land on the North Nile Delta of Egypt by ~60% creating an additional challenge to wheat production in this region.

1. Introduction

Egypt's climate is predominantly arid, with low precipitation of <130 mm per year. The River Nile is the main source of irrigation

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water. The rapidly growing population (90.0 M people in 2015), and a stagnation in wheat yields over the last decade (FAO, 2012), will lead to increased wheat shortages in Egypt. The situation is further compounded by climate change, through both increased temperatures and sea level rise affecting crops. Food security is generally negatively impacted by increasing wheat demand and input prices, soil degradation, greenhouse emissions and competition between land and water (Challinor et al., 2014; Pretty et al., 2010; Hertel, 2011). In the study area, the soil is mainly clay with low hydraulic conductivity, with soil available water-holding capacity of ~21% (Seleiman and Kheir, 2018; Sugita et al., 2017).

Excessive temperature increase due to climate change has negative impacts on wheat productivity and thus on food production (Asseng et al., 2015; Asseng et al., 2018), resulting in hazard impacts on population, particularly in middle income countries (Gao et al., 2019). The main impact of increasing temperature on wheat crop productivity is mainly due to a reduced time from crop emergence to maturity. On the other hand, rising CO_2 might increase crop yield due to enhancing photosynthesis and reducing water use (Deryng et al., 2016) or through improving the lodging resistance of crop by changing physicochemical properties of the basal internodes (Zhao et al., 2018). However, this impact varies according to the corresponding uncertainty by multi-model's ensemble (Wallach et al., 2018) and environments (Dubey and Sharma, 2018).

Like temperature, and CO_2 concentration, sea level rise (SLR) is one of the main direct impacts of climate change on agriculture sector with less attention so far. Many scenarios predict SLR in the 21st century, some of these scenarios predict an increase of 0.8 m by 2095 (IPCC, 2001). Another IPCC prediction scenario in 2007 predicted a SLR of 0.6 m by 2100. The SLR in the 5th IPCC assessment report, was predicted to be 52–98 cm by 2100 (IPCC, 2014). Therefore, there are many SLR scenarios, as each team has different approaches and analysis, but they all agree to SLR due to climate change. One of the most hazardous impacts of SLR on agriculture is the inundation of low-elevation coastal areas (Mcgranahan et al., 2007). The Nile Delta of Egypt is highly vulnerable to inundation through SLR. Marine transgression will decrease the extent of agricultural land and thus decrease crop production and food security (Rotzoll and Fletcher, 2013). Impacts of SLR as a function of climate change have received considerable attention. However, most studies have focused on economic impacts and damage to coastal ecosystems (Darwin and Tol, 2001; Rositasari et al., 2011), with less attention on agriculture and crop production particularly in Egypt.

Crop models are considered useful tools to study and quantify the likely impacts of climate change, as they can link well between different climate variables and crop development processes that are particularly vulnerable to climate change (Wallach et al., 2018). Consequently, models have been widely applied and tested in different studies including impacts of temperature on crop production (Rosenzweig et al., 2014). The Decision Support System for Agrotechnology Transfer (DSSAT) modeling (Jones et al., 2003) is considered the leading and essential models that are widely used in different environments.

The N-Wheat is a wheat model in APSIM and it is a derivative crop synthesis model from CERES, which includes different justifications (Holzworth et al., 2014; Asseng et al., 1998; Ritchie et al., 1998). The first justification option included replacing the crop water uptake system in CERES with another approach depending on the critical fraction of soil available water. It is also possible to replace the function of Leaf Area Index (LAI) and potential evapotranspiration in CERES with connection of water demand to biomass through transpiration efficiency. These model differences could result in simulation differences between CERES-Wheat and N-Wheat models. Climate change and variability usually have negative impacts on agricultural production (Challinor et al., 2007; Müller et al., 2011), and these impacts might be boosted by global warming (Thornton et al., 2010; Wheeler and Von-Braun, 2013) including minor studies in Africa (Cairns et al., 2013; Cooper and Coe, 2011). Egypt is among the most vulnerable countries in Africa due to its arid environment and dependence on the River Nile as its primary water source (Rosenzweig and Hillel, 1994; Rosenzweig et al., 1995). However, these models not tested under Egyptian conditions before particularly for the current variety, creating a research gap in climate change studies.

Wheat is one of the most strategic crops for food and feed. Nevertheless, no previous studies have quantified wheat yields subjected to rising temperature and SLR in the Egyptian coastal areas. In addition, the current recent cultivar (Misr3) is too new high yielding variety and needs further studies to explore its potential resistance to higher temperatures and carbon dioxide concentrations. Therefore, the main objectives of this study were (1) to calibrate and evaluate CERES-Wheat and N-Wheat models with the new high-yielding cultivar (Misr3) under current conditions, (2) to investigate the impacts of increased temperature and CO_2 concentrations and sea level rise on the wheat yield of Misr3 in a major agricultural coastal area of Egypt, and (3) to quantify the total reduction in wheat production under different scenarios of SLR in the study region.

2. Materials and methods

The current investigation includes two DSSAT models calibrated using field experiments conducted through two successive growing seasons in a coastline area in Egypt. Then, the calibrated models were used to predict wheat yields under different scenarios of temperature increase (1, 2, 3 and 4 °C) and elevated CO_2 concentrations (400, 500, 600 and 700 ppm) and compared with baseline yields in the period 1981–2010. As the study area is prominently a low elevation coastline, it is expected to be vulnerable to projected SLR. We therefore quantified the inundation area and thus the reduction in wheat yield due to marine transgression, based on a digital elevation map (DEM) and three potential SLR scenarios (0.5, 1.5 and 2.0 m). These stages could be used as suitable tools to quantify wheat production in a coastline governorate in Egypt subjected to rising temperature, and SLR.

2.1. The study location

The study was conducted on the North Nile Delta of Egypt, Kafr El-Sheikh governorate (KFS), Sakha, which is a coastal area of Northern part of Egypt. The study area is bounded by longitude between 30° 30′ and 31° 20′ E and latitude between 31° 00′ and 31° 30′ N and elevation is ≤6.0 m above sea level (Fig. 1A). Annual rainfall ranges from 100 to 150 mm and annual mean temperature is ~21.5 °C. Soil groups in Egypt have been classified as Aridisol, Entisol and Vertisol (Said, 1993). The dominant soil temperature regime is thermic, and for the dominant soil moisture is torric. We investigated Aridisols, as they form the dominant soil group in this area. Analyzed soil parameters are reported in Tables 1 and 2.

2.2. Field experiment and agricultural practices

A field experiment was conducted at Sakha Agricultural Research Station, Sakha, Egypt during two successive wheat growing seasons in 2014/2015 and 2015/2016. The experiment included a split split plot design with three replicates. The main plots were assigned to planting dates November 20th (the recommended) and November 30th (late). Sub plots were irrigation treatments as a proportion of actual evapotranspiration (ET_c) as 1.5, 1.0 and 0.5. The sub-sub plot treatments were fertilization as a combination between mineral nitrogen and compost as an organic fertilizer as follows:

1- Control (without mineral N fertilization and with 15 t ha^{-1} of compost), N0
2- 100% from the recommended N (120 kg N/ha) with 9.2 t ha^{-1} of compost, N1
3- 70% from recommended N with 11.5 t ha^{-1} of compost, N2
4- 50% from recommended N with 13.8 t ha^{-1} of compost, N3.

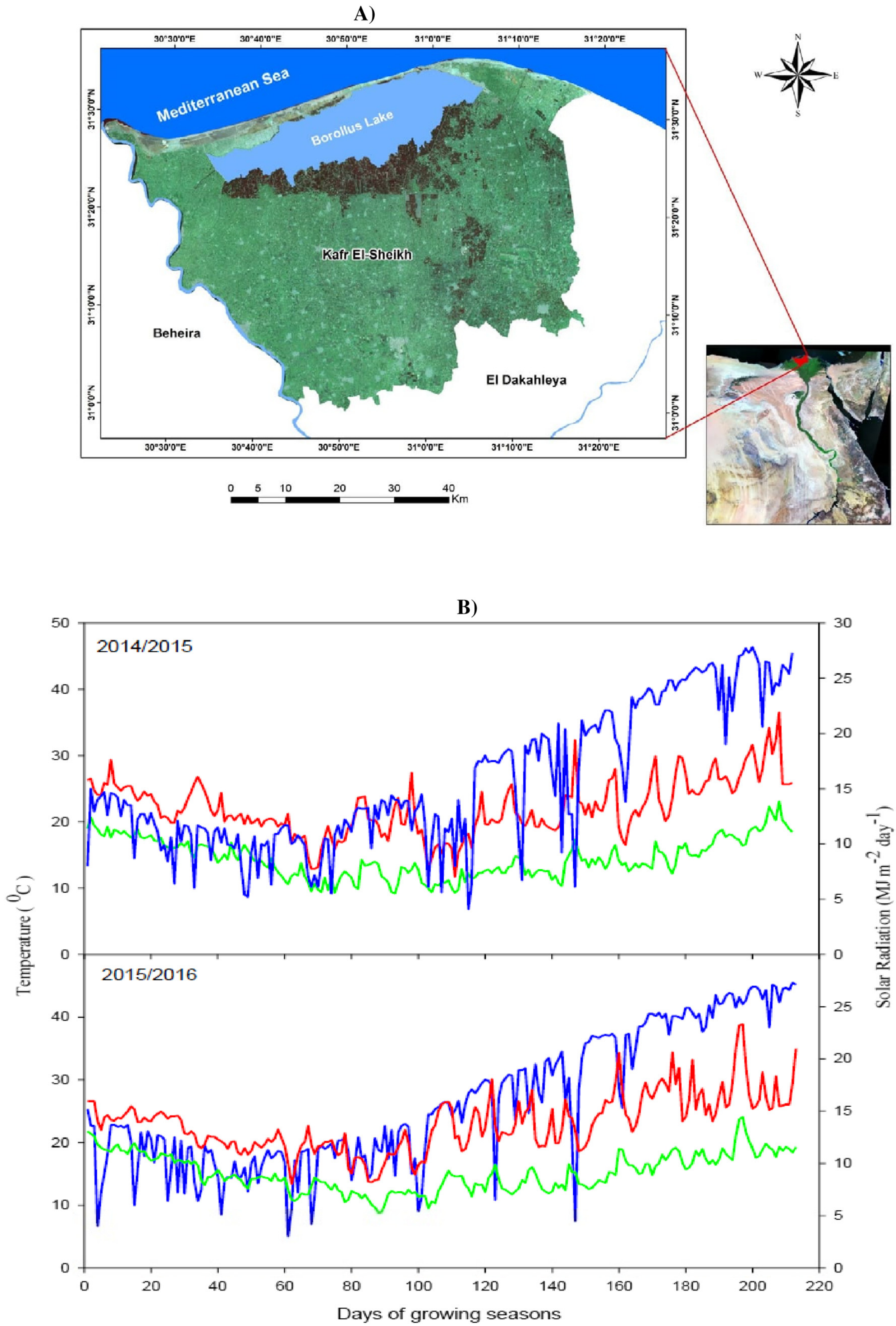

Fig. 1. Location map with country boundaries (A) and site climatic data during wheat growing season (B). In (B), daily maximum temperature (red), minimum temperature (green) and solar radiation (blue) during two growing seasons 2014/2015 and 2015/2016. Daily climatic data were collected from a meteorological station close to the experimental site and belongs to CLAC.

Table 1
Soil physical properties of the studied soils before treatment application.

Soil depth (cm)	Particle size distribution (%)			Texture class	OM (%)	$CaCO_3$ (%)	Water constants (%)		
	Sand	Silt	Clay				FC	WP	AW
0–20	18.7	31.5	49.8	Clay	1.54	2.56	42.9	22.9	19.9
20–40	15.7	32.6	51.7	Clay	1.47	2.43	40.3	19.7	20.5
40–60	16.5	35.1	48.2	Clay	1.13	2.08	38.8	18.9	19.9

Moisture constants such as soil field capacity (FC), wilting point (WP) and available water (AW) were determined for calculating irrigation water applied.
OM: soil organic matter.

A new and common high-yield wheat cultivar (Misr3) was chosen. It is a modern variety and was recently added to the Egyptian cultivars inventory by "The International Maize and Wheat Improvement Center", CIMMYT. Yield and phenology parameters, including grain yield, total final biomass, anthesis date (DAS), and maturity date (DAS), were investigated. These parameters were used to prepare file A in DSSAT models for calibration under current conditions.

2.3. Weather conditions

Daily maximum, minimum temperatures and solar radiation data were obtained from Central Laboratory of Agricultural Climate (CLAC) in Egypt (http://www.clac.edu.eg/) (Fig. 1B). Kafrelsheikh region is located at the first ecological zone in Egypt (coastal zone), which characterizes by thermic soil temperature regime and torric soil moisture regime according to USDA (2010). The maximum temperature during the wheat growing season ranged from 15 to 35 °C, and minimum temperature ranges between 9 and 20 °C. Solar radiation ranged between 3 and 22 MJ m^{-2} day^{-1} (Fig. 1B).

2.4. Crop simulation models

In this study we used the two wheat models CERES-Wheat and N-Wheat (previously APSIM-Wheat) embedded in Decision Support Systems for Agrotechnology Transfer (DSSAT, v 4.7) (Hoogenboom et al., 2015; Jones et al., 2003). These models were chosen based on their global acceptance and confidence in climate change studies (Tubiello and Ewert, 2002). DSSAT models are designed to simulate crop growth as a function of crop features, soil characteristics, weather and management. In this study, both models were calibrated and tested with Misr3 wheat cultivar. Calibration was performed manually through checking the optimum set of parameters in models in the specific location.

2.5. Model applications

Daily baseline climatic data (1981–2010) from NASA, AgCFSR climate dataset (http://data.giss.nasa.gov/impacts/agmipcf/) were used to quantify the projected future wheat yields subjected to different scenarios of temperature (T) and CO_2 concentrations using CERES-Wheat and N-Wheat models under irrigated conditions. The most common approach to investigate the likely impacts of climate change on wheat yield is changing T, CO_2 and moisture, through applying such changes to baseline (Rosenzweig and Parry, 1994). We therefore used different scenarios of T, CO_2 and their interactions to explore the potential impacts of climate change on wheat yield (Table 3). The performance of calibrated models was evaluated using coefficient of determination (R^2), root mean square deviation (RMSD) and model index of agreement (d) as explained by Willmott (1984), Jacovides and Kontoyiannis (1995), and Moriasi et al. (2007).

Table 3
Hypothetical levels of rising temperature and CO_2 on wheat yield at Kafrelsheikh, Egypt.

Scenarios	Parameters
Baseline[a] (1981–2010)	Daily dataset of temperature and rainfall with fixed CO_2 level = 360 ppm during wheat growing season
Temperature change only	+1, +2, +3 and +4 °C
CO_2 level changes only	400, 500, 600 and 700 ppm
Combined changes (temperature and CO_2)	CO_2 level = 400, 500, 600 and 700 ppm Temperature change = +1, +2, +3 and +4 °C

[a] The baseline climatic data for Kafrelsheikh were generated from NASA website.

2.6. SLR impacts on wheat production

The area potentially inundated by SLR was predicted using a digital elevation model (DEM) which was interpolated by its altitude. Identifying the coastal areas that are vulnerable to inundation was determined by the correlation between projected SLR and local topography. Three SLR scenarios were used (IPCC, 2007; Rahmstorf, 2007; Pfeffer et al., 2008), which assume sea level rises of 0.5, 1.5 and 2.0 m. Therefore, we generated a new inundation map using ArcGIS (v 10.22) based on local topography and the severe uncertain scenario (2.0 m), where the pixel value of SLR bigger than or equal to local elevation, that area was identified as vulnerable to inundation.

3. Results

3.1. Calibration and evaluation of CERES-Wheat and N-Wheat models

Ceres-Wheat and N-Wheat crop models were calibrated using the dataset of 2014/2015 growing season and validated using the dataset of 2015/2016 growing season for the Misr3 cultivar. The calibration process was performed manually through modifying only the genetic parameters of the cultivar to accord with the observed dataset under all treatments. The calibrated cultivar parameters for Misr3 for the two models are reported in Table 4. For the calibration process, the genetic parameters have obtained in a step-wise process: (1) phenology, (2) grain yield and (3) biomass. The genetic coefficient of determination was calculated manually using the trial and error method of Godwin and Singh (1998). The values were modified based on reaching the minimum root mean square deviation (RMSD) between predicted and observed data. The calibration of CERES-Wheat and N-Wheat was successful (Fig. 2). The prediction of grain yield, total biomass, anthesis date and maturity date was accurate, with minimum deviation from observed values.

Table 2
Soil chemical properties before treatment application.

Soil depth (cm)	pH	EC[a] (dS/m)	SAR[b]	Soluble cations (meq l^{-1})				Soluble anions (meq l^{-1})				Available NPK (mg kg^{-1})		
				Na^+	K^+	Ca^{+2}	Mg^{+2}	CO_3^{-2}	HCO_3^-	Cl^-	SO_4^{-2}	N	P	K
0–20	8.12	3.18	9.43	21.6	0.7	6.7	3.8	0	2	18	13	62	10.71	249
20–40	8.25	4.53	11.28	30.8	0.9	9.5	5.4	0	3.5	24	19.2	48	9.93	241
40–60	8.39	5.22	12.07	35.5	1.2	11	6.3	0	5.5	27	22	35	8.54	206

[a] EC: electrical conductivity (salinity) in soil paste extract.
[b] SAR: sodium adsorption ratio in soil extract solution.

Table 4
Cultivar parameters of cv. Misr3 calibrated for two crop models.

Models	Parameter names	Parameter definition	Misr3
CERES-Wheat	P1D	Photoperiod sensitivity coefficient	87
	P1V	Vernalization sensitivity coefficient	01
	P5	Thermal time from the onset of linear fill to maturity (°Cd)	370
	G1	Kernel number per unit stem and spike weight at anthesis (kernel g^{-1})	24
	G2	Standard kernel size under optimum conditions (mg)	49
	G3	Tiller death coefficient. Standard stem and spike weight when elongation ceases (g)	1.0
	PHINT	Thermal time between the appearance of leaf tips (°Cd)	100
N-Wheat	VSEN	Sensitivity to vernalization	0.0
	PPSEN	Sensitivity to photoperiod	4.2
	P1	Thermal time from emergence to the end of juvenile (°Cd)	400
	P5	Thermal time from beginning of grain filling to maturity (°Cd)	535
	PHINT	Phyllochron interval	100
	GRNO	Coefficient of kernel number per stem weight at the beginning of grain filling (kernels (g stem)$^{-1}$)	32
	MXFIL	Potential kernel growth rate (mg $kernel^{-1}$ day^{-1})	3.0
	STMMX	Potential final dry weight of a single tiller excluding grain	3.0

The DSSAT models reproduced grain yields well with R^2 values of 0.93 and 0.90 for N-Wheat and CERES-Wheat, respectively. There were an overall root means square deviation (RMSD) of 413 and 346 kg ha^{-1} and a high index of agreement (d) of 0.97 and 0.90 for N-Wheat and CERES, respectively (Table 5). This is an indication that, the models showed the highest yield simulations under the current conditions. Total biomass was also successfully simulated under both models (Fig. 2). R^2 for biomass simulations were 0.80 and 0.60, RMSD values scored 1783.0 and 1648.0 kg ha^{-1}, while d values ranged from 0.70 to 0.80 for N-Wheat and CERES-Wheat respectively (Table 5).

Accordingly, the plotted data of phenological parameters of simulated anthesis and maturity dates (DAS) were generally in agreement

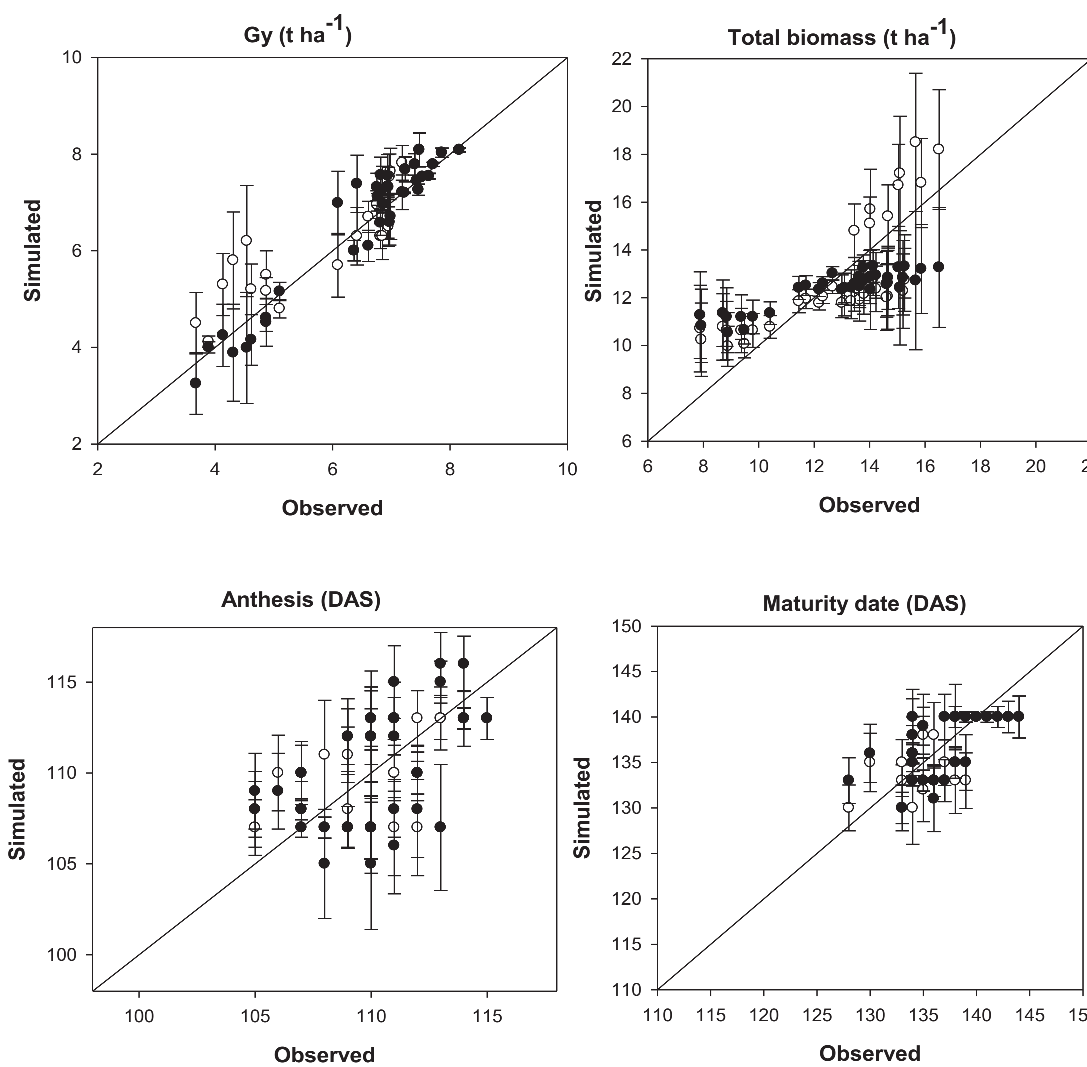

Fig. 2. Calibrations of N-Wheat (black closed circles) and CERES-Wheat (open circles) models under different treatments (planting dates, irrigation and fertilization) in experimental location. Symbols (mean) and error bars (±1 s.d.).

Table 5
Model performance for N-Wheat and Ceres-Wheat for (Misr3) spring wheat at Kafrelsheikh Governorate, Egypt.

Models evaluation indices	N-Wheat model		Ceres-Wheat model	
	Grain yield	Total biomass	Grain yield	Total biomass
R^2	0.93	0.80	0.90	0.60
RMSD (t ha^{-1})	0.413	1.783	0.346	1.648
D	0.97	0.70	0.90	0.80
	Anthesis	Maturity	Anthesis	Maturity
R^2	0.20	0.30	0.30	0.50
RMSD (days)	3	3	3	3
D	0.70	0.70	0.70	0.80

R^2, RMSD and D, are determination coefficient, root mean square deviation and degree of agreement between observed and simulated crop attributes.

(Fig. 2), along with a good agreement of low RMSD and higher d (Table 5). Nevertheless, simulations of maturity of both models were slightly better than those of anthesis, which showed some overestimation, particularly under full irrigation treatment (Fig. 2). Applied water, fertilization treatments and planting dates had significant impacts on observed grain yield, final biomass and phenological parameters and the DSSAT models successfully reproduced these parameters well (Fig. 2). For instance, deficit irrigation, fertilization stress and late planting date decreased grain yield from 8.2 to 3.7 t ha^{-1} and observed total biomass from 16.5 to 7.9 t ha^{-1}. However, the models showed a slight overestimation for final biomass under conditions of insufficient irrigation and fertilization (Fig. 2). This may be attributed to an overestimation of soil water content by both models. Insufficient irrigation and fertilization treatments accelerated the observed anthesis and maturity dates from 115 to 105 for anthesis and from 144 to 128 DAS for maturity. Sensitivity analysis showed an increase in uncertainty expressed as standard deviation errors, particularly under deficit irrigation, fertilization stress and late planting date treatments (Fig. 2).

3.2. Ceres-Wheat and N-Wheat applications: climate variability impacts

Four temperature and CO_2 scenarios were used to study the impacts of climate change on wheat yield, based on baseline climate. Both models predicted crop yields under baseline climate (1980–2010), (Fig. 3). Wheat yield decreased with increasing temperature and decreasing rainfall, and the lowest yield was predicted in the warmest year, 2010.

Rising temperature markedly decreased wheat yields as predicted by both models (Fig. 4A) and the lowest yield was projected under the highest temperature increase (4 °C). Compared with yields under baseline climate, the relative changes of grain yield as a mean prediction by both models were −5.08, −9.35, −13.11, and −17.65% for increasing temperature by +1, +2, +3 and +4 respectively (Fig. 4B). The

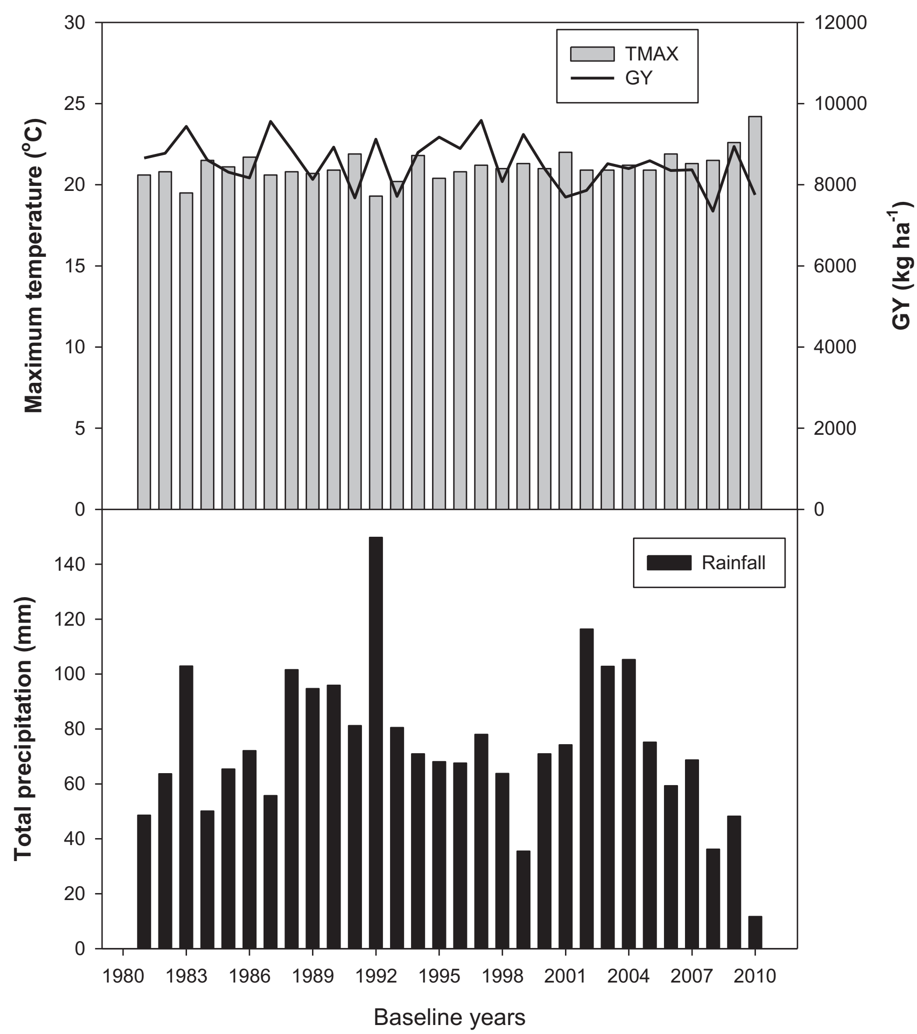

Fig. 3. Wheat grain yield prediction, maximum temperature and total precipitation during the baseline (1981–2010) based on two wheat models. Baseline climatic data generated by NASA website for Kafrelsheikh Governorate (the study area). Potential predicted grain yield (lines) is an average by two models (N-Wheat and CERES-Wheat).

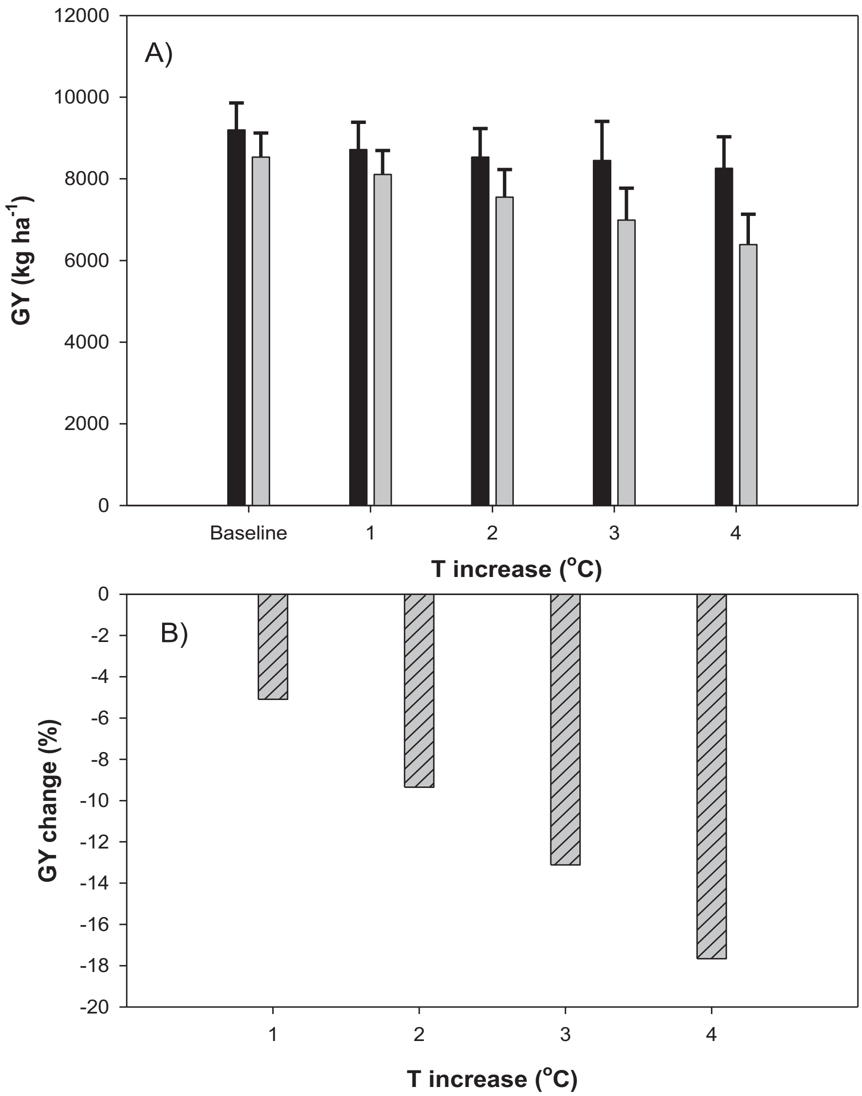

Fig. 4. Impacts of temperature increase on wheat yield (A) and relative change to baseline (B) in the study location based on prediction of two wheat-models. Black and grey bars represent wheat yield prediction by CERES-Wheat and N-Wheat respectively. Error bars represent standard deviation.

performance of both models was similar in predicting wheat yield with higher reliability. Uncertainty expressed as relative standard deviations increased with increasing temperature (Fig. S1). On the other hand, simulations of wheat grain yields using both models under elevated CO_2 concentrations (assuming the yield at 360 ppm as the baseline) projected increased yields (Fig. 5A). The projected wheat grain yield increased by 3.6, 11.9, 19.0 and 25.0% for CO_2 concentrations rising to 400, 500, 600 and 700 ppm respectively, relative to yield at baseline (Fig. 5B). The combined impacts of rising temperature and CO_2 on wheat grain yield found that, under 400 and 500 ppm of CO_2, there are usually negative impacts on wheat grain yield under all temperature scenarios. The exceptions were increased temperature by 1 and 2 °C in the 500 ppm of CO_2, under which projected wheat grain yields increased (Fig. 6A). Elevated CO_2 concentrations to 600 and 700 ppm increased wheat grain yields under all temperature scenarios. However, the increase was at a lower rate under elevated temperatures, but the average change was positive under 600 and 700 ppm of CO_2 levels (Fig. 6B).

3.3. Impacts of SLR on land inundation and loss of agricultural area and wheat production

To explore the impacts of SLR on land inundation, accurate elevation map of the studied area was derived from google earth. The topography of the study area ranges from 0 to 8.0 m above sea level (Fig. S2). Ground water depth data as reported by RIGW (2014), and water quality (expressed as salinity) as determined by FAO (2009), are also presented in Fig. S2. Areas close to the Mediterranean Sea have low elevations, shallow ground water depth and saline ground water. Based on the elevation data and the SLR scenarios, the total inundated areas in KFS were calculated to be 195.65, 158,695.7, and 182,608.7 ha under A1F1, Rahmstorf, and Pfeffer scenarios, respectively (Fig. S4A). Therefore, agricultural land expected to be inundated due to SLR is 0.07, 52.9, and 60.8% for these three scenarios, respectively. Thus, wheat production would be markedly decreased due to the loss of wheat agricultural land through marine transgression (Figs. 8B and S4B).

4. Discussion

CERES-Wheat and N-Wheat crop models can be used successfully to select suitable cultivars and predict probable wheat yields under various climate change scenarios. The phenology of wheat has marked impacts on yield growth and development (Ceglar et al., 2011). The models realistically simulated wheat phenology using the specific model indices (Fig. 2 and Table 4). In N-Wheat, anthesis time was controlled by VSEN and PPSEN, while maturity dates were determined by P5 (Table 4). Therefore, phenology calibration of wheat in the N-Wheat

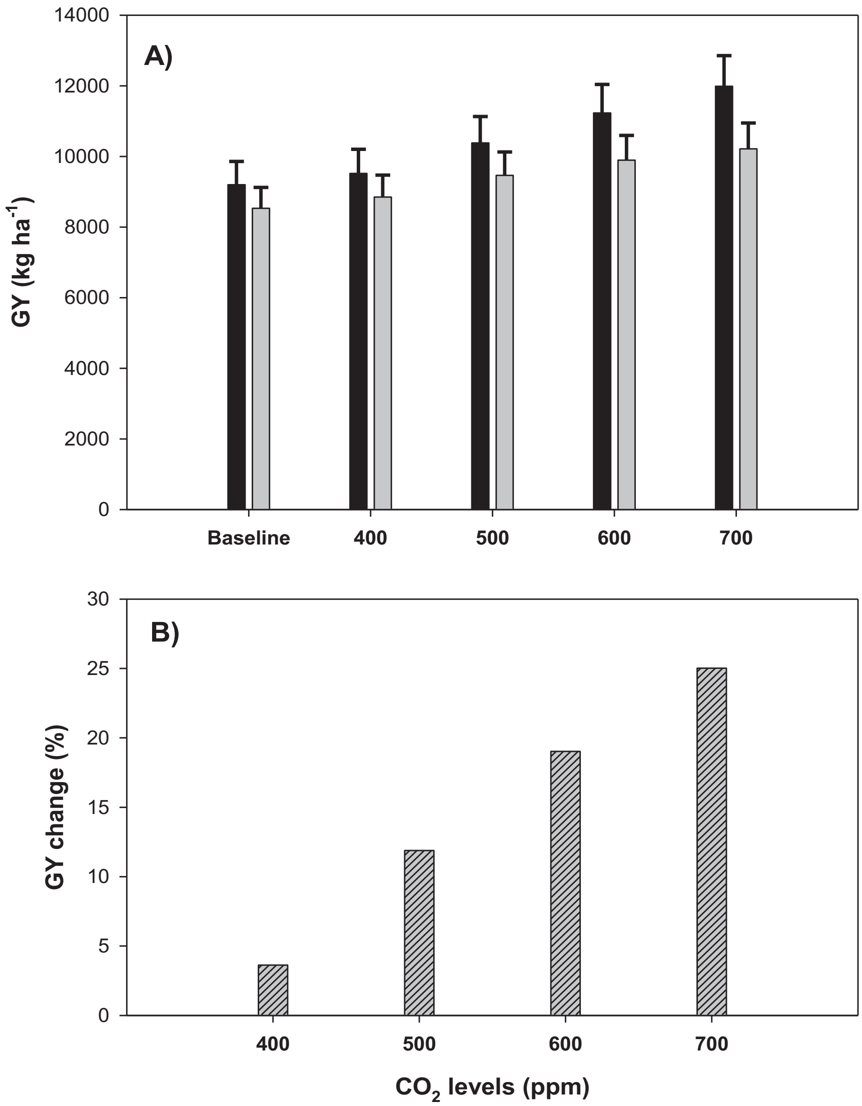

Fig. 5. Impacts of increasing CO_2 concentrations on wheat yield (A) and yield change (B) relative to baseline yield (1981–2010) using two wheat models. Black and grey bars represent wheat yield prediction by CERES-Wheat and N-Wheat respectively. Error bars represent standard deviation.

model needs these three parameters (Asseng et al., 1998, 2013, 2015). P1V, P1D, P5 and Phint are necessary to control and justify phenology in CERES-Wheat (Andarzian et al., 2015). Changing P1, P2, P3 and P4 in the ecotype file is mainly required for model reliability (Johnen et al., 2012), indicating that wheat phenology could be determined by temperature and photoperiod variables (Aslam et al., 2017). High quality calibration can be achieved by ensuring accurate phenology data (Archontoulis et al., 2014; Ahmed et al., 2016). By achieving high phenology accuracy, genotypic variations could be captured by models which affect yield, biomass and leaf area development (Robertson et al., 2002). Solar radiative interception and radiative use efficiency are the main factors controlling the biomass production. Our findings resulted in accurate estimates of biomass production (Arora et al., 2007), due to the positive relationship between biomass and grain yield (Dettori et al., 2011).Biomass in this study was controlled by STMMX and G3 for both N-wheat and CERES-Wheat models respectively (Table 4).

Grain yield is related to the interception of solar radiation by crop canopy, radiation use efficiency and harvest index. Both models achieved a convincing simulation of grain yield. In N-Wheat the calibration of grain yield was controlled using GRNO and MXFIL parameters. Meanwhile, the required parameters in CERES-Wheat are G1, G2 and G3 (Hunt and Boote, 1998). This calibration step should follow the phenology calibration (Ma et al., 2011). Although we used only one year of data for model calibration and another year for validation, the simulation achieved a reliability calibration with high accuracy (Fig. 2 and Table 5). This is mainly attributed to the quality of observed data and conducting the experiment in one agroclimatic zone (zone 1) with less variability in climate between locations. In a similar way, Asseng et al. (2018) calibrated three DSSAT models using only one season achieving a robust calibration. Simulation modeling is a complex process, involving interactions of multiple factors including soil, climate and crop variables. However the simulations might contain uncertainties associated with individual crop model (Kassie et al., 2016). Quantifying the uncertainty in a single crop model is problematic, particularly considering likely climate change impacts on crop yield (Rotter et al., 2011; Asseng et al., 2013). Consequently, ensemble multi models for simulations have been suggested to quantify the model uncertainty (Martre et al., 2015; Wallach et al., 2018). For instance, by expanding existing model platforms (Feng et al., 2014), an additional wheat model (N-Wheat) has been added to the current wheat models on DSSAT platform (Kassie et al., 2016). In this study, ensemble of two models (CERES and N-Wheat) showed a high robust simulation with less uncertainty (Fig. S1).

Although ensemble of multiple models is very important for decision makers (Rosenzweig, 2013), DSSAT models like other crop models have some limitations, particularly regarding the effect of diseases and pests on crop development. These limitations require further analysis and discussion of model simulations. We therefore, quantified uncertainty under elevated temperatures (Fig. S1).

The soils developed on the Nile Delta are known globally and the coastal area covers >5000 km^2, thus creating potential vulnerability to SLR (Fig. S3). Furthermore, climate change, particularly rising temperature, might add additional challenges to wheat production on the Delta. The KFS is considered representative of coastal Egypt and so the analysis has broader implications for agro-environmental policy on the Nile Delta.

There was a decline in wheat grain yield during the baseline (1981–2010), which predicted by both models due to increased temperatures. The lowest wheat yield was predicted in the warmest year (2010) (Fig. 3). Our analysis suggests that climate change in KFS, especially increased temperatures will decrease future wheat yields (Fig. 4). This is mainly due to accelerating crop development and decreasing biomass (Asseng et al., 2015), Furthermore, temperature increase could shorten the crop life cycle (Sayre et al., 1997) and thus decrease the interception of solar radiation (Heng et al., 2007; Alexandrov and Hoogenboom, 2000). It appears realistic that a 1.0 °C temperature increase would decrease wheat grain yield by approximately 6.0%, which accords the findings of Asseng et al. (2015). On the other hand, increasing CO_2 concentrations would probably increase wheat grain yield (Fig. 5). This is mainly due to increasing the rate of photosynthesis or in other words, increasing cellular CO_2 concentrations, which is mainly responsible for minimizing stomatal conductance and decreasing transpiration rates (Asseng et al., 2004). As we can't separate impact of temperature from CO_2 in nature, the combined effect of both T and CO_2 has been explored. The combined impacts of increased CO_2 and temperature increased predicted wheat grain yield, but after 3 °C increase, there is a predicted decline in wheat yield only under 400 and 500 ppm of CO_2. Meanwhile, under elevated CO_2 concentrations to 600 and 700 ppm, there is a predicted increase in wheat grain yield under all investigated scenarios of increased temperature (Fig. 6). These findings suggest that the impact of higher temperatures could be alleviated by elevated CO_2, particularly with the most resistant cultivars, such as Misr3. However, there is uncertainty from temperature

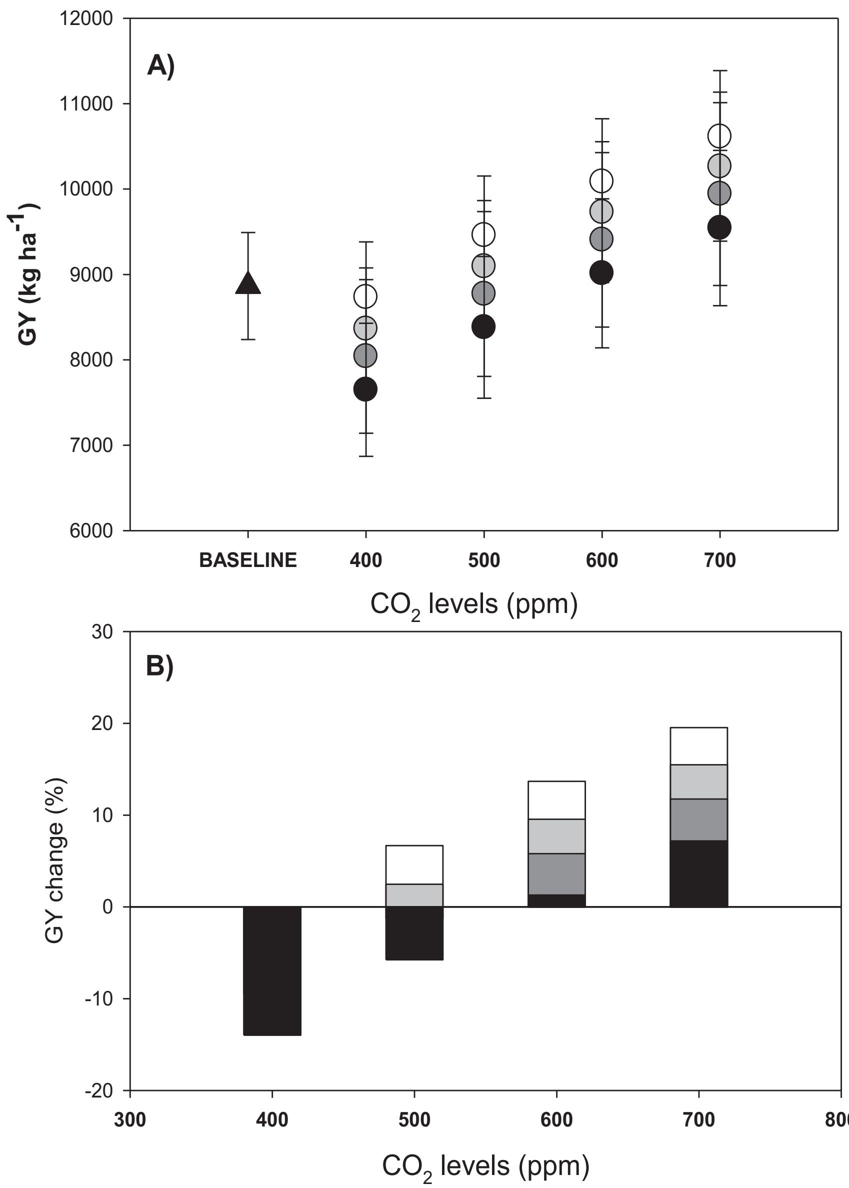

Fig. 6. Combined impact of temperature and CO_2 increases on wheat yield (A) and change percentage of wheat relative to baseline (B). Black triangle refers to baseline, while colors white, grey, dark grey and black refer to temperature increase by 1, 2, 3 and 4 respectively (symbols, mean; error bars, ±1 s.d.).

increase ranged between 8 and 9.5% (Fig. S1). Increasing wheat grain yield in response to elevated CO_2 had been achieved by improving grain numbers in spike (Dias de Oliveira et al., 2015). On the suggested mechanisms are increased net leaf photosynthetic rate and the availability of carbon assimilations in the floret due to elevated CO_2. Consequently, floret death rates decreased, and grain number increased by 42%. Therefore, they suggested the possibility of breeding new resistant cultivars that have more florets, thus responding to increased CO_2 fertilization under high temperature and drought conditions. Our findings concluded that, the Misr3 cultivar has many florets and responded to elevated CO_2 concentrations, which compensated for higher temperatures. Therefore, the growth stimulus under higher concentrations of CO_2 will not be overtaken by the negative impact on yield of rising temperatures, particularly for recent resistant cultivars. For more discussions, data presented in Fig. S5, showed a marked increase in wheat grain numbers, particularly under elevated CO_2 concentrations ≥ 600 ppm, even at high temperatures. This could be due to decreasing floret death rates with increasing CO_2, so the higher temperatures were mitigated by elevated CO_2 concentrations. This indicates the potential of the Misr3 cultivar for resistance to high temperatures due to its response to CO_2 fertilization. However, the CO_2 growth stimulus, could be less as suggested in the simulation (and in short- term field experiments), as recently been indicated in long-term experiments in which the growth stimulus from elevated CO_2 concentration in C3 grasses declined over the years (Reich et al., 2018).

Alongside the temperature and CO_2 impacts on wheat yield in KFS, there is another negative impact of SLR due to climate change. The direct physical impact of SLR on wheat production in KFS appears through the loss of agricultural land due to inundation by marine transgression. Currently, the total irrigated area in KFS is ~300,000 ha, and the extent of wheat cultivated area is ~90,000 ha (FAO, 2015). Thus, the wheat agricultural area represents about 34% from the total irrigated area. To quantify the total wheat production in KFS, the mean crop yields in all other districts alongside the current experimental site is required. Therefore, wheat yield for all other districts in KFS was obtained from farmers and prepared by Ministry of Agricultural and Land Reclamation in Egypt (MALR, 2016) (Fig. 7). The estimated mean wheat grain yield for all districts was 7.15 t ha^{-1}. Based on the total wheat agricultural area (90,000 ha) and the average wheat yield (7.15 t ha^{-1}), the total wheat production in KFS is estimated to be ~643,500 t. This quantity is expected to be decreased by SLR through land inundation. Our findings quantified the loss of agricultural land due to inundation under different scenarios of SLR (Figs. S4A and 8A). The expected loss of total agricultural land due to SLR by inundation is 0.07, 52.9, and 60.8% if sea level rose by 0.5, 1.5, and 2.0 m respectively, leading to decreasing the wheat agricultural area (90,000 ha) to be 89,937, 42,390 and 35,280 ha under 0.5, 1.5 and 2.0 m scenarios of SLR respectively. Consequently, based on the calculated inundated wheat area from total inundated area, wheat production in KFS will decrease by 0.09, 76.7, and 88.3% under A1F1, Rahmstorf, and Pfeffer scenarios respectively, (Fig. 8B). In addition to further reduction of wheat yield in response to SLR, there would be also major losses due to rising temperature, which would be especially high under medium concentrations of CO_2. Therefore, major decreases in wheat production in KFS are feasible due to the combined effects of SLR and increased temperatures. These effects require the government, scientists and decision-makers to develop viable mitigation and adaptation plans.

5. Conclusions

Egypt has relatively few studies of climate change, hence projections of the probable impacts of climate change on wheat production and food security are uncertain. Moreover, Kafrelsheikh province is a major agricultural and coastal area in Egypt and is especially vulnerable

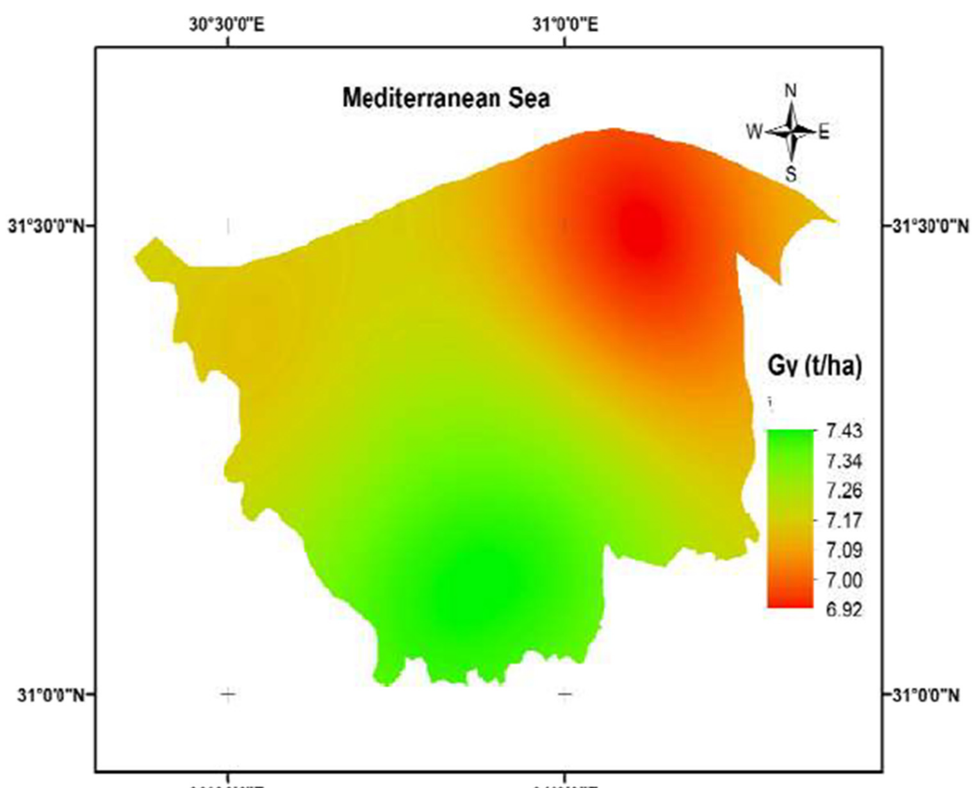

Fig. 7. Wheat farmer's yield in Kafrelsheikh Province (MALR, 2016). Wheat yields (at 10% grain moisture). Wheat yield in all districts in KFS (interpolated color) was collected by Ministry of Agricultural and Land Reclamation through initiative program. Decrease yield towards North (low temperature) is mainly due to salinity impact by Mediterranean Sea.

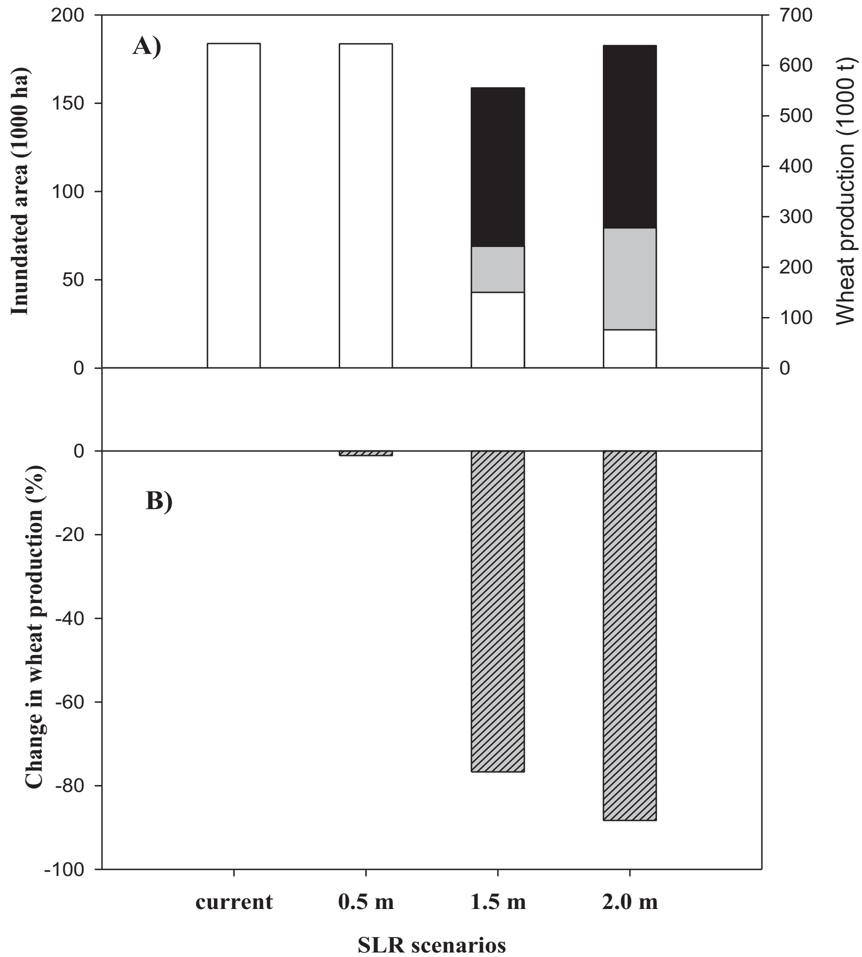

Fig. 8. Wheat production (open bar, A), wheat inundated area (grey bar, A) and total agricultural inundated area (black bar, A) as well as relative change in wheat production in response to inundation (B) under different scenarios of SLR in Kafrelsheikh governorate (the study area).

to marine inundation. Quantifying the impacts of increasing temperature and SLR on wheat production in KFS can help the decision- makers seeking for alternative options to minimize agro-environmental damage. Ensemble of two DSSAT wheat models (CERES-Wheat and N-Wheat) was used for calibration and evaluation using a recent wheat cultivar (Misr3) and field experimental data. To achieve the further objectives, different agronomic treatments included planting dates, irrigation and fertilization were conducted in a two-successive wheat growing seasons. Both models were successfully calibrated under irrigated conditions achieving robustness in model evaluation indices with grain yield and phenology. Following calibration, different climate change scenarios of rising temperature, CO_2 concentrations and the combination of increasing temperature and CO_2 under irrigated conditions in Egypt were analyzed using the models. The substantial results predicted decreased wheat grain yield with rising temperature, while increased CO_2 concentrations projected an increase in wheat yield. The combined effect of temperature and CO_2 projected an increase in wheat yield under higher concentrations of CO_2, meanwhile under low concentrations of CO_2, the negative impact due to temperature was clear. Results suggest that the Misr3 cultivar could be particularly resistant, as it has many florets and is responsive to higher concentrations of CO_2 under warming conditions. Another threat of climate change impacts on wheat production in the study area is sea level rise. Three scenarios of SLR and their impacts on land inundation and hence on the loss of agricultural land were studied. The substantial results showed that, a big area of agricultural land would be lost due to inundation in response of SLR. The lost agricultural area had quantified by ~60% from the total agricultural land under the risky scenario of SLR (2.0 m). Consequently, the total wheat production in KFS will be reduced strongly due to climate change either by rising temperature or by SLR, requiring great efforts from scientists and decision makers to look for the potential solutions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.10.209.

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